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# Income Growth in U.S. States: Is it Pro-Poor?

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## **Income Growth in U.S. States: Is it Pro-Poor?**

### **Introduction**

Economic growth has always been a subject of interest to economists, politicians, and the general public alike. An economy growing at a modest rate is seen as healthy, while an economy that is not growing or experiencing negative growth is seen as unhealthy. However, the growth of an economy is not simply seen as good in and of itself, but rather to what extent it contributes to the well being of its citizens.

While it is generally assumed that economic growth will have a positive effect the vast majority of the population, this claim is often left unchallenged. In particular, the effect of economic growth on the low-income segment of the population is not well understood. In particular, it is not clear if 1) the poor benefit from economic growth, and if so 2) what is the size of the benefit? A growing number of studies have been devoted to answering these questions. This field of study is commonly known as the pro-poor growth literature.

Before a more in depth examination of the literature and its findings, it is necessary to first address the importance of pro-poor growth. In particular, one might question the relevance of pro-poor growth, when the growth rate of the gross domestic product (GDP) is readily available and commonly used to assess the growth of an economy. Doesn't this measure provide a reasonable proxy for growth in all segments of the society? While the GDP growth rate does serve its purpose to state how much the level of economic activity has grown, it has inherent shortcomings that limit its ability to accurately reflect the growth experienced by a representative cross sample of society. As

it appears, standard measures of GDP growth put less weight on income growth of low-income individuals relative to high-income individuals (Ram 2007).

To illustrate this point consider the example in Table 1, which shows units of income for each quintile in fictitious countries A and B for two years. To clarify, each quintile represents the units of income for a given fifth of the population, with the Lowest Quintile showing the income of the poorest fifth and the Highest Quintile showing the income for the richest fifth. The Total GDP is the sum of the incomes of each of the quintiles, while the GDP growth rate is percent change in Total GDP from year 1 to year 2. As one can see, GDP growth rate for Country A is 7.14 percent, which is twice the 3.57 percent growth rate of Country B.

Since the total GDP growth rate for Country A is twice the rate of Country B, one might conclude that the income of each fifth of Country A's population increased more than the income for each fifth of Country B's population. However, a closer inspection of the table shows that this conclusion is incorrect. In fact, only the richest two quintiles in Country A experienced more growth than in Country B. Therefore, higher overall GDP growth does not necessarily imply higher income growth for all segments of the population. As a result, GDP growth does not provide a good measure of economic well being for all segments of the population.

## **Literature Review**

Chenery et al. (1974) recognized this limitation of the GDP growth rate and proposed distributional weighting to account for this difference. Distributional weighting corrects for this weakness by assigning different weights to the income growth of

different income percentiles. While any weighting can be used, a common method is to assign equal weighting to each income percentile. When using quintiles, this means that each quintile's income growth represents 20% of the country's overall growth rate<sup>1</sup>.

While distributional weighting has been used on a limited basis, it has established groundwork for further studies on pro-poor growth. Other early works that have helped to lay the foundation for future studies in pro-poor growth include Pen (1971) and Watts (1968). Pen discusses the distribution of income across the population and describes in dramatic fashion this distribution by using the illustration of “a parade formed by many dwarfs and a few giants” (1971) where a participant's height represents his or her income level.

Watts (1968) addresses the correct measurement of poverty. While the contribution by Watts (1968) is described less dramatically, it is nonetheless significant. Specifically, he devised a measurement for poverty that is highly regarded and used to device other poverty measures (Ravallion and Chen 2003; Zheng 1993).

The subject of pro-poor growth received limited attention from 1971 to 1996. However, it has received renewed interest since then. One notable study is Deininger and Squire (1996), which is widely cited and commonly regarded as the seminal paper on the issue. Deininger and Squire compiled a data set containing country-level incomes and income shares, which has allowed researchers to perform econometric analysis on pro-poor growth over a wide sample. Deininger and Squire find that 1) the poor benefit from economic growth and that 2) economic growth has no discernible relationship with inequality (Deininger and Squire 1996).

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<sup>1</sup> A mathematical model for this measure, referred to as distributional weighting, will be discussed further in the Data section.

From this point forward, the study of pro-poor growth diverges onto two different paths depending on how one defines poverty. The first path studies absolute poverty, which is often measured as the number of people below a given level of income. Research along this path has studied how the number of people below the poverty line changes as a result of economic growth. My research does not focus on this path, but it is worth noting that available evidence suggests that the number of people below the defined poverty line falls as a result of economic growth (Ravallion and Chen 1997; Adams 2002; Ravallion and Datt 2002; Kraay 2004). However, the magnitude of this change depends on where one draws the poverty line (Ravallion and Chen 1997; Ravallion 2004). Furthermore, Chen and Ravallion (2001) find that only the East Asian and Middle East/North African regions experienced a decrease in the number of people below the absolute poverty line, while other regions experienced either no significant change or an increase in the number of people below the poverty line.

The other path taken by pro-poor growth literature examines relative poverty. This line of research focuses either on the income growth of the poor relative to the entire population (Deininger and Squire 1996; Foster and Szekely 2001; Dollar and Kraay 2002; Jenkins and Kerm 2003; Son 2004) or the relationship between inequality and growth (Barro 2000; Kakwani and Pernia 2000; Lundberg and Squire 2003). While each study assesses pro-poor growth slightly differently and not surprisingly reaches slightly different conclusions, the general finding is that the poor benefit from growth (Deininger and Squire 1996; Barro 2000; Kakwani and Pernia 2000; Foster and Szekely 2001; Dollar and Kraay 2002; Jenkins and Kerm 2003; Lundberg and Squire 2003; Son 2004).

However, there is disagreement on the size of the benefit. To illustrate, consider the studies by Dollar and Kraay (2002) and Foster and Szekely (2001), which reach different conclusions<sup>2</sup>. The former study finds that the income growth for the poor is not significantly different from the income growth rate for the general population (2002). In contrast, Foster and Szekely (2001) find that the income growth rate of the poor was lower than the income growth for the entire population. While Foster and Szekely (2001) acknowledge that the growth rate for the bottom 20% of the population is not statistically different from the whole population, using a broader measure they find the rate of pro-poor growth to be statistically significantly less than the rate of overall growth. As is appears, the debate on the magnitude of pro-poor growth is far from settled. Thus, further examination of the subject is necessary.

This paper contributes to this literature by examining pro-poor growth using data from U.S. states over the period 1977-2005. Currently, only one paper has examined pro-poor growth on a sub-national level (Ravallion and Datt 2002). Ravallion and Datt study the change in absolute poverty in different Indian states, whereas this paper will study the relative poverty changes for U.S. states. Building upon existing research, I will use three different pro-poor growth measures: 1) distributional weighting (Chenery et al. 1974); 2) the growth rate of the bottom 20% of the population (Dollar and Kraay 2002; Son 2004); and 3) inverse quintile weighting (Foster and Szekely 2001). Given the limitations associated with each method, the use of these three alternatives provides a more complete picture of pro-poor growth.

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<sup>2</sup> The measurement details for these studies will be included in the Data section.

## Theoretical Model

The standard model to measure pro-poor growth, as in Dollar and Kraay (2002), Son (2004), and Foster and Szekely (2001), is as follows:

$$\bar{y}_{it}^p = \alpha + \beta \bar{y}_{it} + e_{it} \quad (1)$$

Where  $\bar{y}_{it}^p$  is a measure of poor income for state  $i$  at time  $t$ ,  $\bar{y}_{it}$  is the average income of the population for state  $i$  at time  $t$ , and  $e_{it}$  is an iid error term with zero mean and constant variance. The parameter of interest for this equation is  $\beta$ . If  $\beta=1$ , a 1% growth in overall income will contribute to a 1% growth in the poor income. While if  $\beta>1$ , the poor benefit proportionately more than the average, and if  $\beta<1$  the poor benefit proportionately less than the average. Similarly, if  $0<\beta<1$  the poor benefit from income growth but at a rate that is less than the average for the population. However, if  $\beta=0$  the poor will not benefit from overall income growth, and if  $\beta<0$  the poor are adversely affected by overall income growth.

## Data

Estimation of equation (1) requires data on average income for the poor ( $\bar{y}_{it}^p$ ) and overall average income ( $\bar{y}_{it}$ ). Data obtained from the U.S. Census Bureau contains average income and average income for each income quintile, which allows  $\bar{y}_{it}^p$  and  $\bar{y}_{it}$  to be calculated for all states and the District of Columbia for the period 1977-2005. This data has been inflation-adjusted to current 2005 dollars using data from the St. Louis Federal Reserve Bank Internet Database.

In this study, I use three measures of  $\bar{y}_{it}^p$ :  $\bar{y}_{it}^Q$ ,  $\bar{y}_{it}^H$ , and  $\bar{y}_{it}^D$ . Where:

$\bar{y}_{it}^Q$  = Mean income for the bottom quintile in state  $i$  at time  $t$

$\bar{y}_{it}^H$  = Harmonic mean income for state i at time t

$\bar{y}_{it}^D$  = Distributionally-weighted mean income growth rate for state i at time t.

Similarly, I will measure  $\bar{y}_{it}$  using two alternative measures:  $\bar{y}_{it}$  and  $\bar{y}_{it}^G$ . Where:

$\bar{y}_{it}$  = Mean income for state i at time t

$\bar{y}_{it}^G$  = Growth in mean income for state i at time t.

*(1) Income of Bottom Quintile ( $\bar{y}_{it}^Q$ )*

This measure is constructed following Deininger and Squire (1996) and Dollar and Kraay (2002) and is theoretically supported by Son (2004). The strength of this measure is that it allows the researcher to directly access how income of the poorest quintile is affected by overall income growth. In other words, when the population as a whole experiences an increase in income, does a proportion of the population remain relatively poor, or does, in general, everyone benefit proportionately.

One weakness of this measurement is that it arbitrarily uses the poorest quintile to define the poor and does not consider how the incomes of others who may fall just above of the bottom quintile change with a change in mean income. Since the change in mean income of the bottom 20% is likely similar to the change in mean income for the bottom 21%, 25%, or 30%, it may be regarded by some as an acceptable method with only one minor weakness. However, as discussed in depth by Foster and Szekely (2001), this minor weakness creates a noteworthy problem, which they refer to as subgroup inconsistency, in some instances.

Surprisingly, the mean income of the bottom fifth—the income standard employed in many studies, including Dollar and Kraay (2000)—does not satisfy subgroup consistency. This is immediately seen with the help of a numerical



example. Suppose that each of the distributions  $x$ ,  $y$ ,  $x'$  and  $y'$  has ten incomes, with the lowest three incomes being (4, 8, 12), (2, 6, 8), (2, 11, 12), and (3, 6, 8), respectively. Then, the mean of the lowest fifth (or lowest two incomes) is 6 for  $x$  and 4 for  $y$ , with a level of 5 for the combined distribution  $(x, y)$ . However, while the income standards rise to 6.5 for  $x'$  and 4.5 for  $y'$ , the overall standard falls to 4.75 for the combined distribution  $(x', y')$ . This problem arises because of the endogenous nature of the set of the poor implicit in this standard of living. Recall that in the above example, the second lowest income in  $x$  rises significantly enough to compensate for the decline in the lowest income. However, this increase goes unnoticed in the combined distribution since the rising income is elevated outside the set of poor incomes, allowing the remaining decrement to dominate. (Foster and Szekely 2001)

As their example demonstrates, there are instances when an increase in income of poor individuals actually causes the mean income of the bottom quintile to decrease if it causes these individuals to move up to the 2nd-lowest quintile while simultaneously moving others with lower incomes down into the lowest quintile. Therefore, this measurement may sometimes result in inaccuracies. However, this does not completely invalidate this measurement because, as described above, it provides researchers with valuable information about how a growth in mean income affects the income of the lowest quintile.

## (2) *Harmonic Mean* ( $\bar{y}_i^H$ )

Foster and Szekely (2001) develop a new measure of pro-poor growth that is free from the possible inaccuracies of the bottom quintile measure. Their measure, based on

the idea of general means, is referred to as the harmonic mean. I will use a variation of their equation for use with quintile-level data as follows:

$$\bar{y}_{it}^H = [(\bar{y}_1^{-1} + \dots + \bar{y}_n^{-1})/n]^{-1} \quad (2)$$

Where:

$$\bar{y}_1 \dots \bar{y}_n = \text{Mean income of first through } n\text{th income groups}$$

According to (5), the harmonic mean inversely weights the incomes of each quintile. That is, the incomes of the lower quintiles are weighted more heavily than the incomes of the higher quintiles, which each receive a declining weight. Thus, the harmonic mean can also be referred to as the poverty-weighted mean.

A significant strength of the harmonic mean over the income of the bottom quintile is that with the harmonic mean a growth in income of the poor always causes a positive harmonic mean growth rate, and a reduction in the income of the poor always causes a negative harmonic mean growth rate (Foster and Szekely 2001).

However, the harmonic mean is not without its shortcomings. First, the harmonic mean calculation using quintile-level data is statistically weaker than calculating the harmonic mean using individual-level data. However, since individual data was not available for U.S. states, using quintile data is the best that can be done.

There are two other potential arguments against the use of the harmonic mean. First, some may argue that the poverty-weighted mean should not be used as a proxy for the pro-poor growth rate because the income growth of high-income individuals is included in the calculation. While the income of low-income individuals is weighted more strongly than the income of high-income individuals, the inclusion of upper income quintiles in the calculation can be argued against on the grounds that changes in their

income have no bearing on income changes of the poor and thus should not be included in a pro-poor growth measurement.

Second, the opposite side of the above argument would hold that the harmonic mean does not accurately reflect the income growth of the population and instead simply gives the income growth of poor individuals. Of course, this is one major reason for using the harmonic mean as a way to measure the pro-poor growth rate. However, it may be argued that a calculation to assess the overall income growth of individuals in the economy which is not weighted more heavily to high-income or low-income individual income gains should be developed. For this perspective, the harmonic mean does not qualify. Instead, a different measurement technique should be used that weights all income gains equally.

### *(3) Distributionally-Weighted Income Growth ( $\bar{y}_it^D$ )*

Distributionally-weighted income growth, developed by Chenery et al. (1974), is flexible income measurement calculation that allows the researcher to choose the weight he or she assigns to income growth in each quintile. When the income growth rate in each quintile is weighted equally, the distributionally-weighted income growth rate serves as an alternative to the standard mean income growth rate to assess the overall income growth of individuals in the economy. Unlike the standard mean, which places a heavy emphasis on the income growth of higher-income individuals, and the poverty-weighted income growth rate, which places a heavy emphasis on the income growth of lower-income individuals, the distributionally weighted income growth rate weights the rates of income growth of all quintiles equally. The calculation for distributionally weighted income growth rate is as follows:

$$\bar{y}_{it}^D = [0.20(\frac{\bar{y}_{1,t-1} - \bar{y}_{1,t-1}}{\bar{y}_{1,t-1}}) + \dots + 0.20(\frac{\bar{y}_{5,t-1} - \bar{y}_{5,t-1}}{\bar{y}_{5,t-1}})] \quad (3)$$

Where:

$\bar{y}_{n,t}$  = Mean of the nth income quintile at time t

$\bar{y}_{n,t-1}$  = Mean of the nth income quintile at time t-1

According to the equation, the distributionally-weighted income growth is a simple average of the income growth rates for each of the income quintiles.

One advantage of the distributionally weighted income growth rate is that it serves as a viable alternative to the standard mean income growth rate to assess the income growth of individuals in the society. However, because the growth rate of upper-income quintiles is given equal weighting to the growth rate of lower-income quintiles, some may see it as a poor proxy to use to measure the pro-poor growth rate.

### Empirical Model

To determine the relationship between mean income and the income of the poor, equation (1) will be estimated using time-series data for each of the 50 states and the District of Columbia using the three aforementioned measures. These equations are as follows:

$$\bar{y}_{it}^Q = \alpha + \beta \bar{y}_{it} + e_{it} \quad (4)$$

$$\bar{y}_{it}^H = \alpha + \beta \bar{y}_{it} + e_{it} \quad (5)$$

$$\bar{y}_{it}^D = \alpha + \beta \bar{y}_{it}^G + e_{it} \quad (6)$$

For equations (4) and (5), the natural log of  $\bar{y}_{it}$ ,  $\bar{y}_{it}^Q$ , and  $\bar{y}_{it}^H$  will be used to follow econometric convention and previous pro-poor growth papers (Deininger and

Squire 1996; Foster and Szekely 2001; Dollar and Kraay 2002). For equation (6),  $\bar{y}_{it}^D$  is a growth rate in percent form, thus it does not make sense to regress it on  $\bar{y}_{it}$ , as is done in the previous equations. Instead, it is regressed on the mean income growth rate,  $\bar{y}_{it}^G$ .

In order to estimate these equations, one needs to pay attention to the stochastic properties of the variables. Therefore, I will first test for the unit roots of these variables following the Augmented Dickey-Fuller technique. The results are reported in Table 2. For almost all states, the null hypothesis that  $\bar{y}_{it}$  is non-stationary cannot be rejected<sup>3</sup>. For  $\bar{y}_{it}^Q$  and  $\bar{y}_{it}^H$ , the null hypothesis of non-stationarity can be rejected in only about half of the cases<sup>4</sup>. Since there is evidence that all of the variables in equations (4) and (5) are non-stationary<sup>5</sup>, this allows these two equations to be estimated using first-differenced data. For  $\bar{y}_{it}^G$  and  $\bar{y}_{it}^D$ , which are income growth rates, non-stationarity is strongly rejected. Thus, equation (6) does not need to be estimated using first-differenced data.

## Results

### *Income of Bottom Quintile ( $\bar{y}_{it}^Q$ )*

The results for equation (4) are shown in Table 3.1. Recall that to determine the relationship between overall mean income ( $\bar{y}_{it}$ ) and the mean income of the poorest quintile ( $\bar{y}_{it}^Q$ ) the null hypotheses of  $\beta=0$  and  $\beta=1$  are tested. In 39 of 51 states,  $\beta=0$  is

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<sup>3</sup> The only exceptions to this are as follows. For Alaska and Montana, non-stationarity of  $\bar{y}_{it}$  is rejected at the 5% level and for New Mexico and Wyoming it is rejected at the 10% level.

<sup>4</sup> For  $\bar{y}_{it}^Q$ , non-stationarity is rejected in 26 cases at the 5% level and 34 cases at the 10% level. For  $\bar{y}_{it}^H$ , non-stationarity is rejected in 15 cases at the 5% level and 22 cases at the 10% level.

<sup>5</sup> This is also intuitive due to the fact that these are all income variables being studied over time.

rejected at the 10% level<sup>6</sup>. This means that in 39 states a change in the overall mean income has a positive and significant effect on the mean income of the bottom income quintile. However in 12 states,  $\beta=0$  cannot be rejected. For these 12 states, a change in overall mean income does not have a significant effect on the income of the bottom quintile.

In the test of  $\beta=1$ , the null hypothesis cannot be rejected at the 10% level in 45 of 51 states. This means that in 45 states a 1% change in overall mean income causes a 1% change in the mean income of the poorest quintile. However, there are six states where  $\beta=1$  is rejected<sup>7</sup>. For these states, a 1% change in overall mean income causes a less than 1% change in mean income of the poorest quintile.

One final observation of the results is of the wide variation of  $\beta$  from -0.096 in North Dakota to 2.195 in Montana. The interpretation of these coefficients is that in North Dakota a one-percent increase in mean income causes a -0.096 percent decrease in the mean income for the bottom 20% of the population<sup>8</sup>, while in Montana a one-percent increase in mean income causes a 2.195 percent increase in the income for the bottom 20% of the population. This variation in beta coefficients is likely larger than many would intuitively think.

#### *Harmonic Mean ( $\bar{y}_{it}^H$ )*

In order to test the robustness of the results from equation (4), equation (5) was also run to determine the relationship between the harmonic mean ( $\bar{y}_{it}^H$ ) and overall mean income ( $\bar{y}_{it}$ ). These results are shown in Table 3.2. The results show that  $\beta=0$  is rejected

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<sup>6</sup> For each of these states,  $\beta>0$ .

<sup>7</sup> For each of these states,  $\beta<1$ .

<sup>8</sup> This change is not significantly different from zero.

at the 10% level for 44 of 51 states. Thus,  $\beta=0$  was rejected for five more states than it was in equation (4). For the test of  $\beta=1$ , in 39 states the hypothesis cannot be rejected at the 10% level. This means that in equation (5), while most states still exhibit a one-to-one relationship between overall mean income and mean income of the poor, it is found in fewer states than equation (4). Finally, the range of  $\beta$  is between 0.060 for North Dakota and 1.639 for Montana. While this is still a larger range than one might expect, it is less than what was found for equation (4).

*Distributionally Weighted Income Growth ( $\bar{y}_{it}^D$ )*

To further test the robustness of results, the distributionally-weighted income growth ( $\bar{y}_{it}^D$ ) is regressed on the mean income growth ( $\bar{y}_{it}^G$ ), as specified in equation (6). These results are reported in Table 3.3. When testing  $\beta=0$ , the hypothesis is rejected in each of the 51 states at the 5% level<sup>9</sup>. Thus, for equation (6) there is strong evidence that mean income growth has a significant effect on the distributionally-weighted income growth. In the test of  $\beta=1$ , the hypothesis cannot be rejected at the 10% level for 34 states. Thus, while the null hypothesis of  $\beta=1$  can be rejected in more states than equation (4) or (5), it can still not be rejected for a majority of the states.

Finally, it is worth mentioning the range of  $\beta$  between states. For equation (6) the range is from 0.497 in North Dakota to 1.180 in Montana. This is much less variation than was found in equations (4) and (5). However, since North Dakota and Montana continue to have the lowest and highest  $\beta$  values respectively, it points to the idea that the relative relationship of  $\beta$  between the states remains fairly consistent. This suggests that while the magnitude of  $\beta$  changes depending upon whether equation (4), (5), or (6)

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<sup>9</sup> It was rejected at the 1% level for all states except South Dakota.

is tested, the relationship between overall mean income and the variable used to represent the income of the poor ( $\bar{y}_t^p$ ) remains relatively consistent.

### **Analysis and Conclusions**

Since  $\beta$  is significantly greater than zero for the vast majority of states in each of the three equations, one conclusion that can be reached is that there is strong evidence that mean income growth has a positive effect on the income growth of the poor. This means that as overall income grows, the income of the poor grows as well. When considering the original research question of whether or not the poor benefit from economic growth, this points to the conclusion that, in general, the poor do benefit from economic growth.

The second research question asked how much the poor benefit from economic growth. Specifically, is the income growth of the poor proportional to the income growth of the general population? Since  $\beta=1$  cannot be rejected for most states, this suggests that the income growth of the poor is proportional to the income growth of the entire population for these states.

However, while  $\beta=1$  cannot be rejected for most states, there is other evidence that suggests that, in general,  $\beta<1$ . First, while significance levels do not allow the rejection of  $\beta=1$ , this may be due to having too few state-level observations and too much variance within these observations to reject  $\beta=1$  even if  $\beta>1$  most of the time.



Specifically, for each of the three equations, many more states have  $\beta$ -values of less than 0.85 than have  $\beta$ -values of greater than 1.15<sup>10</sup>.

Second, in order to increase the degrees of freedom and draw some conclusions about pro-poor growth for the entire country, a panel-data model that included all of the states was run. For equations (4), (5), and (6), both a fixed-effect and random-effect model was run, and the Hausman Test was used to determine the more appropriate model for each equation<sup>11</sup>. The panel data results are found in Table 4. They show that  $\beta$  is significantly less than one for each of the equations. This means that, for the country as a whole, the income growth rate of the poor is less than the income growth rate of the general population.

Next, while I did generalize pro-poor growth to the entire country for the purposes of the previous results, the large variation of  $\beta$ -values between states is evidence that pro-poor growth studies should concentrate on state or sub-national levels instead of generalizing them at the national level. The only previous study that I am aware of that studies pro-poor growth on a sub-national level is Ravallion and Datt (2002), which studies pro-poor growth in different Indian states. Thus, there is much potential for further sub-national pro-poor growth studies in other countries around the world.

Finally, due to time and data accessibility limitations my research does not test any possible determinants for different poor income growth rates between states. Further studies could test different determinants to figure out what is causing variations between

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<sup>10</sup> For equation (4),  $\beta < 0.85$  for 25 states and  $\beta > 1.15$  for 9 states. For equation (5),  $\beta < 0.85$  for 28 states and  $\beta > 1.15$  for four states. For equation (6),  $\beta < 0.85$  for 22 states and  $\beta > 1.15$  for one state.

<sup>11</sup> For equations (4) and (5), the fixed-effect model was more appropriate. For equation (6), the random effect model was more appropriate.

states. Some possible determinants to consider are initial overall income, initial income of the poor, traditional economic growth determinants (e.g. education, capital, technology, etc.), and state-level public policies (e.g. minimum wage, tax rates, welfare programs, etc.). Combined with the results of this paper, further studies can help researchers understand the relationship between overall income and the income of the poor with hopes of better understanding the complex dynamics of poverty.

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## Tables

**Table 1**

	Year	Total GDP	Lowest Quintile	2nd-Lowest Quintile	Middle Quintile	2nd-Highest Quintile	Highest Quintile
Country A	1	700	20	50	100	190	340
	2	750	20	50	105	205	370

**Country 1 GDP growth rate: 7.14%**

	Year	Total GDP	Lowest Quintile	2nd-Lowest Quintile	Middle Quintile	2nd-Highest Quintile	Highest Quintile
Country B	1	700	20	50	100	190	340
	2	725	25	55	105	195	345

**Country 2 GDP growth rate: 3.57%**

## Table 2

State	$\bar{y}_{it}$	$\bar{y}_{it}^Q$	$\bar{y}_{it}^H$	$\bar{y}_{it}^G$	$\bar{y}_{it}^D$
Alabama	-1.071	-2.154	-1.645	-7.454 ***	-7.027 ***
Alaska	-3.119 **	-3.086 **	-3.120 **	-5.856 ***	-5.105 ***
Arizona	-1.673	-3.253 **	-2.795 *	-5.280 ***	-4.907 ***
Arkansas	-0.928	-1.865	-1.676	-5.490 ***	-6.425 ***
California	-0.827	-2.189	-1.747	-4.078 ***	-3.769 ***
Colorado	-1.359	-3.071 **	-2.503	-6.194 ***	-5.675 ***
Connecticut	-1.914	-2.787 *	-2.925 *	-6.212 ***	-5.799 ***
Delaware	-2.060	-3.863 ***	-3.142 **	-6.662 ***	-6.213 ***
District of Columbia	-1.364	-3.932 ***	-3.720 **	-5.518 ***	-4.895 ***
Florida	-0.814	-2.534	-2.088	-4.936 ***	-4.175 ***
Georgia	-1.905	-2.630 *	-2.322	-6.319 ***	-5.482 ***
Hawaii	-1.792	-3.136 **	-3.077 **	-6.287 ***	-5.549 ***
Idaho	-0.953	-2.393	-1.867	-4.796 ***	-5.310 ***
Illinois	-0.956	-2.522	-2.154	-4.341 ***	-4.389 ***
Indiana	-1.008	-2.786 *	-2.426	-4.653 ***	-4.608 ***
Iowa	-0.842	-1.817	-1.543	-5.987 ***	-5.084 ***
Kansas	-1.590	-4.225 ***	-3.997 ***	-5.358 ***	-6.262 ***
Kentucky	-1.134	-2.590	-2.271	-5.044 ***	-4.563 ***
Louisiana	-2.583	-3.185 **	-2.997 **	-7.559 ***	-7.154 ***
Maine	-1.658	-4.292 ***	-3.837 ***	-6.510 ***	-5.960 ***
Maryland	-0.959	-4.211 ***	-4.056 ***	-4.599 ***	-5.882 ***
Massachusetts	-0.918	-3.058 **	-2.979 *	-5.376 ***	-5.373 ***
Michigan	-1.133	-2.469	-2.267	-3.873 ***	-4.295 ***
Minnesota	-1.024	-2.366	-1.784	-6.605 ***	-6.550 ***
Mississippi	-0.940	-2.858 *	-2.209	-5.698 ***	-5.810 ***
Missouri	-1.333	-2.598	-2.123	-7.414 ***	-5.879 ***
Montana	-2.939 **	-5.162 ***	-5.290 ***	-6.948 ***	-7.331 ***
Nebraska	-0.609	-3.112 **	-2.645 *	-5.717 ***	-6.660 ***
Nevada	-1.969	-5.535 ***	-4.949 ***	-8.942 ***	-9.010 ***
New Hampshire	-1.274	-4.364 ***	-2.510	-5.342 ***	-5.616 ***
New Jersey	-0.358	-2.349	-1.500	-4.445 ***	-3.510 **
New Mexico	-2.810 *	-4.070 ***	-3.676 **	-7.326 ***	-6.492 ***
New York	-0.772	-2.664 *	-2.313	-5.305 ***	-3.935 ***
North Carolina	-0.968	-2.374	-2.276	-3.739 ***	-3.783 ***
North Dakota	-1.158	-2.460	-2.413	-7.224 ***	-5.532 ***
Ohio	-1.383	-3.764 ***	-3.116 **	-5.517 ***	-6.375 ***
Oklahoma	-1.481	-3.970 ***	-3.227 **	-6.593 ***	-7.622 ***
Oregon	-1.594	-2.633 *	-2.324	-6.826 ***	-6.626 ***
Pennsylvania	-0.538	-2.776 *	-2.209	-4.883 ***	-4.187 ***
Rhode Island	-1.216	-3.135 **	-2.351	-5.437 ***	-4.836 ***
South Carolina	-1.958	-3.378 **	-2.899 *	-6.481 ***	-6.865 ***
South Dakota	-1.061	-4.655 ***	-3.834 ***	-6.163 ***	-7.747 ***
Tennessee	-0.969	-2.328	-1.743	-5.578 ***	-4.757 ***
Texas	-1.294	-3.330 **	-2.971 *	-5.527 ***	-5.650 ***
Utah	-1.137	-2.170	-1.733	-6.318 ***	-6.001 ***
Vermont	-1.333	-3.446 **	-2.617	-5.190 ***	-4.499 ***
Virginia	-0.947	-3.286 **	-2.225	-3.826 ***	-3.903 ***
Washington	-1.171	-2.703 *	-2.604	-6.303 ***	-5.011 ***
West Virginia	-1.480	-3.108 **	-2.965 *	-4.532 ***	-4.322 ***
Wisconsin	-1.454	-2.543	-2.233	-5.423 ***	-5.024 ***
Wyoming	-2.691 *	-4.207 ***	-3.469 **	-6.969 ***	-8.444 ***
Reject null hypothesis of non-stationarity at the					
1% level ***					
5% level **					
10% level *					

<b>Table 3.1</b>				
$\bar{y}_{it}^Q$				
State	$\beta$	Std. Error	T-Value ( $\beta=0$ )	T-Value ( $\beta=1$ )
Alabama	-0.071	0.322	-0.220	-3.326 ***
Alaska	0.937	0.546	1.717 *	-0.116
Arizona	0.501	0.326	1.534	-1.530
Arkansas	1.105	0.379	2.920 ***	0.278
California	0.846	0.283	2.987 ***	-0.546
Colorado	1.491	0.324	4.605 ***	1.516
Connecticut	0.938	0.378	2.481 ***	-0.164
Delaware	0.872	0.188	4.646 ***	-0.681
District of Columbia	0.385	0.519	0.741	-1.185
Florida	0.808	0.304	2.657 ***	-0.631
Georgia	1.124	0.217	5.167 ***	0.568
Hawaii	1.148	0.242	4.739 ***	0.612
Idaho	1.225	0.316	3.882 ***	0.714
Illinois	1.106	0.273	4.058 ***	0.390
Indiana	1.367	0.362	3.782 ***	1.016
Iowa	0.833	0.328	2.541 ***	-0.508
Kansas	1.067	0.145	7.337 ***	0.461
Kentucky	1.471	0.354	4.154 ***	1.330
Louisiana	0.119	0.380	0.314	-2.319 **
Maine	0.969	0.344	2.819 ***	-0.089
Maryland	0.744	0.368	2.024 *	-0.695
Massachusetts	0.254	0.269	0.942	-2.774 ***
Michigan	1.200	0.348	3.448 ***	0.574
Minnesota	1.301	0.166	7.843 ***	1.816
Mississippi	0.526	0.291	1.808 *	-1.631
Missouri	0.845	0.315	2.682 ***	-0.492
Montana	2.195	0.605	3.626 ***	1.974
Nebraska	1.315	0.440	2.988 ***	0.716
Nevada	0.944	0.629	1.501	-0.089
New Hampshire	0.382	0.391	0.978	-1.579
New Jersey	0.784	0.338	2.316 **	-0.639
New Mexico	1.001	0.360	2.780 ***	0.002
New York	0.729	0.223	3.277 ***	-1.217
North Carolina	0.929	0.247	3.769 ***	-0.286
North Dakota	-0.096	0.484	-0.198	-2.264 **
Ohio	0.847	0.389	2.179 **	-0.393
Oklahoma	0.760	0.293	2.590 ***	-0.819
Oregon	0.508	0.222	2.289 **	-2.216 **
Pennsylvania	0.684	0.460	1.486	-0.686
Rhode Island	0.860	0.164	5.251 ***	-0.856
South Carolina	0.696	0.325	2.146 **	-0.935
South Dakota	0.681	1.177	0.578	-0.271
Tennessee	0.529	0.349	1.515	-1.347
Texas	1.005	0.256	3.928 ***	0.020
Utah	0.875	0.247	3.547 ***	-0.506
Vermont	0.679	0.362	1.875 *	-0.887
Virginia	0.250	0.330	0.757	-2.273 **
Washington	0.671	0.290	2.311 **	-1.133
West Virginia	1.062	0.281	3.782 ***	0.221
Wisconsin	1.061	0.239	4.445 ***	0.255
Wyoming	1.465	0.395	3.705 ***	1.175
*Significant at 10% Level				
**Significant at 5% Level				
***Significant at 1% Level				

<b>Table 3.2</b>				
$\bar{y}_{it}^H$				
State	$\beta$	Std. Error	T-Value ( $\beta=0$ )	T-Value ( $\beta=1$ )
Alabama	0.192	0.225	0.854	-3.596 ***
Alaska	0.902	0.362	2.491 ***	-0.270
Arizona	0.567	0.234	2.426 **	-1.856 *
Arkansas	0.996	0.241	4.139 ***	-0.015
California	0.849	0.190	4.459 ***	-0.792
Colorado	1.190	0.195	6.119 ***	0.979
Connecticut	0.854	0.275	3.110 ***	-0.530
Delaware	0.785	0.120	6.558 ***	-1.793 *
District of Columbia	0.444	0.383	1.161	-1.453
Florida	0.720	0.220	3.272 ***	-1.270
Georgia	0.977	0.162	6.014 ***	-0.142
Hawaii	1.012	0.167	6.074 ***	0.074
Idaho	0.997	0.160	6.215 ***	-0.020
Illinois	0.999	0.183	5.459 ***	-0.003
Indiana	1.066	0.275	3.883 ***	0.241
Iowa	0.768	0.208	3.700 ***	-1.117
Kansas	0.941	0.130	7.267 ***	-0.454
Kentucky	1.205	0.255	4.730 ***	0.806
Louisiana	0.287	0.272	1.056	-2.623 **
Maine	0.850	0.236	3.608 ***	-0.636
Maryland	0.738	0.242	3.053 ***	-1.085
Massachusetts	0.442	0.192	2.300 **	-2.904 ***
Michigan	1.079	0.239	4.514 ***	0.332
Minnesota	1.105	0.095	11.582 ***	1.096
Mississippi	0.599	0.201	2.981	-1.997 *
Missouri	0.763	0.212	3.597 ***	-1.116
Montana	1.639	0.352	4.656 ***	1.815
Nebraska	1.054	0.348	3.025 ***	0.155
Nevada	0.745	0.437	1.704	-0.583
New Hampshire	0.669	0.233	2.869 ***	-1.417
New Jersey	0.743	0.261	2.847 ***	-0.985
New Mexico	0.911	0.242	3.770 ***	-0.370
New York	0.690	0.164	4.202 ***	-1.891 *
North Carolina	0.878	0.197	4.457 ***	-0.617
North Dakota	0.060	0.305	0.196	-3.087 ***
Ohio	0.836	0.233	3.593 ***	-0.704
Oklahoma	0.645	0.190	3.390 ***	-1.868 *
Oregon	0.459	0.134	3.419 ***	-4.028 ***
Pennsylvania	0.674	0.332	2.029 *	-0.981
Rhode Island	0.764	0.152	5.024 ***	-1.556
South Carolina	0.743	0.221	3.355 ***	-1.161
South Dakota	0.565	0.762	0.741	-0.571
Tennessee	0.509	0.244	2.091 **	-2.015 *
Texas	0.873	0.173	5.041 ***	-0.735
Utah	0.880	0.140	6.294 ***	-0.862
Vermont	0.630	0.290	2.169 **	-1.276
Virginia	0.444	0.225	1.971 *	-2.465 **
Washington	0.819	0.207	3.957 ***	-0.873
West Virginia	1.015	0.191	5.303 ***	0.077
Wisconsin	1.002	0.152	6.577 ***	0.011
Wyoming	1.215	0.249	4.874 ***	0.861
*Significant at 10% Level				
**Significant at 5% Level				
***Significant at 1% Level				

<b>Table 3.3</b>				
$\bar{y}_{it}^D$				
State	$\beta$	Std. Error	T-Value ( $\beta=0$ )	T-Value ( $\beta=1$ )
Alabama	0.630	0.095	6.642 ***	-3.900 ***
Alaska	0.926	0.157	5.899 ***	-0.472
Arizona	0.764	0.115	6.663 ***	-2.059 **
Arkansas	0.967	0.104	9.299 ***	-0.316
California	0.906	0.085	10.645 ***	-1.103
Colorado	1.010	0.077	13.152 ***	0.125
Connecticut	0.882	0.124	7.113 ***	-0.955
Delaware	0.850	0.056	15.162 ***	-2.677 **
District of Columbia	0.669	0.180	3.713 ***	-1.841 *
Florida	0.790	0.101	7.864 ***	-2.085 **
Georgia	0.929	0.080	11.670 ***	-0.890
Hawaii	0.940	0.077	12.196 ***	-0.775
Idaho	0.934	0.066	14.158 ***	-1.007
Illinois	0.957	0.075	12.779 ***	-0.572
Indiana	0.948	0.166	5.728 ***	-0.312
Iowa	0.838	0.087	9.580 ***	-1.851 *
Kansas	0.924	0.075	12.395 ***	-1.026
Kentucky	1.010	0.124	8.127 ***	0.080
Louisiana	0.623	0.118	5.282 ***	-3.194 ***
Maine	0.860	0.106	8.073 ***	-1.318
Maryland	0.854	0.112	7.637 ***	-1.303
Massachusetts	0.739	0.086	8.615 ***	-3.045 ***
Michigan	0.976	0.107	9.105 ***	-0.227
Minnesota	1.002	0.038	26.634 ***	0.061
Mississippi	0.775	0.095	8.132 ***	-2.368 **
Missouri	0.840	0.093	9.014 ***	-1.711 *
Montana	1.180	0.135	8.772 ***	1.341
Nebraska	0.942	0.168	5.596 ***	-0.342
Nevada	0.808	0.210	3.842 ***	-0.914
New Hampshire	0.859	0.085	10.119 ***	-1.661
New Jersey	0.831	0.129	6.415 ***	-1.307
New Mexico	0.920	0.101	9.082 ***	-0.786
New York	0.782	0.079	9.933 ***	-2.770 ***
North Carolina	0.919	0.097	9.444 ***	-0.828
North Dakota	0.497	0.127	3.905 ***	-3.948 ***
Ohio	0.902	0.095	9.504 ***	-1.030
Oklahoma	0.749	0.084	8.920 ***	-2.983 ***
Oregon	0.655	0.057	11.456 ***	-6.026 ***
Pennsylvania	0.806	0.167	4.836 ***	-1.166
Rhode Island	0.821	0.100	8.205 ***	-1.787 *
South Carolina	0.868	0.094	9.201 ***	-1.395
South Dakota	0.719	0.329	2.189 **	-0.853
Tennessee	0.709	0.107	6.628 ***	-2.722 **
Texas	0.862	0.082	10.545 ***	-1.692
Utah	0.926	0.058	15.828 ***	-1.274
Vermont	0.764	0.157	4.861 ***	-1.499
Virginia	0.745	0.096	7.778 ***	-2.655 **
Washington	0.934	0.107	8.710 ***	-0.620
West Virginia	0.989	0.089	11.067 ***	-0.125
Wisconsin	0.974	0.062	15.621 ***	-0.424
Wyoming	1.041	0.113	9.201 ***	0.362
*Significant at 10% Level				
**Significant at 5% Level				
***Significant at 1% Level				



<b>Table 4</b>			
	Equation (4)	Equation (5)	Equation (6)
Fixed-Effect $\beta$	0.55	0.58	0.86
Random-Effect $\beta$	0.58	0.61	0.86
Hausman Test (chi-squared value)	37.64 <sup>1</sup>	95.03 <sup>1</sup>	0.00 <sup>2</sup>
T-Value ( $\beta=0$ )	22.63 <sup>3</sup>	34.54 <sup>3</sup>	61.53 <sup>3</sup>
T-Value ( $\beta=1$ )	-18.20 <sup>3</sup>	-24.66 <sup>3</sup>	-10.36 <sup>3</sup>
<sup>1</sup> Fixed-Effect Model appropriate <sup>2</sup> Random-Effect Model appropriate <sup>3</sup> Reject the null hypothesis at the 1% level			